Towards the determination of surface collapse type over abandoned mines in the Lorraine iron basin

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ABSTRACT:
Surface collapse is a major problem that follows many active or abandoned underground workings. Collapses result from roof deformation of underground workings, and/or controlled or uncontrolled rock caving. The uncontrolled rock caving could result in surface instability problem and loss of materials and/or human life. Over the past 90 years, and as result of underground-uncontrolled rock caving, 16 major accidents "surface collapse" has been reported in the French Lorraine iron basin. Some of these collapses were sudden and violent "happened over few minutes and up to few hours", led to loss of life in some cases, while others occurred progressively "within few days", with fewer effects on the surface environment.
The sudden occurrence of these accidents is of big interest in order to be able to predict the risk induced by abandoned underground mines in this basin especially in areas where cities built and people live.
The objective of this study is to try, with the aid of data analysis techniques, to define a criterion of rapidity of the accident where it is probable to occur according to the principal underground workings' geometry. This analysis was accomplished using Principal Component Analysis (PCA) and Discriminant Analysis (DA).
With respect to the small number of accidents that had happened, we were able to define general criteria of the type of accident to be expected, using essentially the site's geotechnical and exploitation properties

1 INTRODUCTION

The French Lorraine's iron basin extends over 1500 square kilometers in the eastern part of France. Figure 1 shows a geographical situation map of the basin. The basin had been worked out since the 19th and 20th centuries. The method of exploitation consisted of rooms and pillars of various shapes followed by integral stooping.

In cases where the remained pillars were taken off, surface collapse occurred in a more or less controlled way, and in order to consider surface structures (houses, roads, infrastructure, etc.), the method of exploitation consisted of leaving in place "enough" amount of pillars (varying from 80% to 30%) in order to prevent uncontrolled collapse from occurring.

Unfortunately, the percentage of pillars left in place depended largely on the experience rather than depending on long-term stability analysis.

During the 20th century, we were able to localize and report 16 accidents of unpredicted collapses in the basin. Eight of them happened in a sudden and brutal way and led in sometimes to loss of life, while others happened in a progressive way and led only to the destruction of houses and infrastructures.

The increased concern of regional authority led us to try to define for the basin (where geological situations are almost the same) a criterion of discrimination between situations (underground workings) where brutal collapse are likely to happen and others where progressive ones are to be expected.

In order to be able to define this criterion over the basin, we have started with a back-analysis over the 16 cases already happened and tried to draw any geological, geotechnical, or geometrical aspects.

Then with the results obtained from this back analysis, we performed a statistical data analysis taking into consideration all available information.

With the aid of techniques like Principal Components Analysis (PCA) and Discriminant Analysis (DA), we were able to define such criterion, but were very sensible to the number of individuals used (16 accidents).

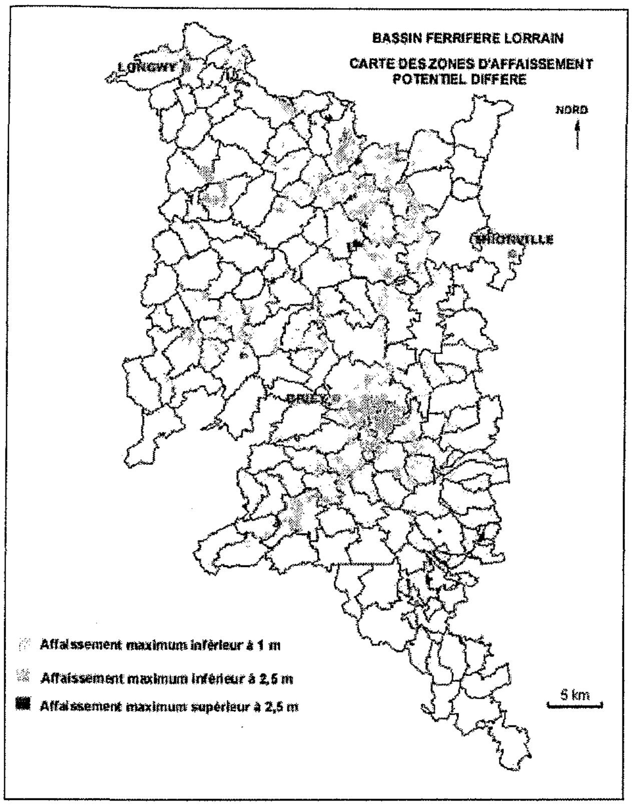

Figure 1. Geographical situation of the Lorrain iron basin

2 GEOLOGICAL AND GEOTECHNICAL ASPECTS

Tincelin (1959) pointed out that in order to expect a brutal collapse, three geological conditions have to take place. These three conditions are;

1. the existence of a hard rock seam at the roof of the extracted iron bed;
2. the existence of a hard rock seam near the surface;
3. and the existence of an adjacent valley.

According to our geological study of the accidents' areas, we were not able to prove that these criterions are discriminant due to the fact that in many situations where progressive collapse happened, these three conditions were also present. This fact allowed us to say that there might be some geological conditions that could favour the existence of brutal collapse, but we cannot just rely only on these three conditions for an overall discrimination in the basin.

One of the major problems that we have faced in working out on the back analysis is that in two adjacent situations, with the same geotechnical and geological conditions, brutal and progressive collapses occurred. This fact led us to conclude that not only geotechnical and geological conditions can discriminate between these two types of collapse, but they have to be coupled with geometrical conditions of extraction (ratio between extracted ore and ore left in place, size of pillars, depth, etc.).

3 STATISTICAL DATA ANALYSIS

3.1 *Data collection and preparation*

Table 1 shows the matrix of collected variables that we were able to make after the back analysis of the 16 accidents (we will call them individuals from here after).

These collected variables in the subsided zones included measured or observed variables:

- length of pillars (m) *"Lng_P"*;
- width of pillars (m) *"Lrg_P"*;
- width of rooms (m) *"Lrg_G"*;
- depth of the subsided zone (m) *"H"*;
- thickness of exploited seams (m) *"W_cum"*;
- whether the subsided zone is adjacent to other zones of exploitation *"C_surch"* coded as 1 for a virgin zone, 2 for a zone adjacent to a caved zone, and 3 for a zone surrounded by caved zones.

The collected variables included also calculated variables that have physical significance:

- ratio between volume extracted and volume left in place (%) *"Defruit"*, calculated as:

$$\text{Taux} = \frac{\text{Lng\_P} \times \text{Lrg\_P}}{(\text{Lng\_P} + \text{Lrg\_G}) \times (\text{Lrg\_P} + \text{Lrg\_G})} \tag{1}$$

- surface of pillar (m^2) *"Surface"*;
- Hydraulic diameter of pillars (m) *"D_Hydr"*, calculated as:

$$\text{D\_Hydr} = \frac{\text{Surface}}{(\text{Lng\_P} + \text{Lrg\_P}) \times 2} \tag{2}$$

- maximum natural stress on pillars (MPa) *"Sig_tot"*, calculated as:

$$\text{Sig\_tot} = \frac{0.025 \times \text{H}}{(1 - \text{Taux})} \tag{3}$$

- buckling of pillars *"El_P"*, calculated as:

$$\text{El\_P} = \frac{\text{W\_Cum}}{\text{Lrg\_P}} \tag{4}$$

We have also assigned an ID for each individual and a variable called type of observed collapse *"Type"* has been added to the matrix of observed/calculated variables.

Table 1. Matrix of observed/calculated values

ID	Name and year	Defruit (%)	H (m)	W_Cum (m)
Aud 02	Audun-le Tiche 1902	0,7	122	13,5
Esch 19	Escherange 1919	0,65	170	6
StMar 32	Sainte-Marie 1932	0,65	153	5
Mou 40	Moutiers 1940	0,7	121	11
Jar 49	Jarny 1949	0,56	200	5
Ron 54	Roncourt 1954	0,7	147	7,5
Ron 59	Roncourt 1959	0,75	140	5
Aub 72	Auboué 1972	0,45	150	6
Roch 73	Rochonvillers 1973	0,62	190	4,5
Roch 74	Rochonvillers 1974	0,61	190	4,5
Crus 77	Crusnes 1977	0,5	180	3,8
Vill 82	Ville-au-Montois 1982	0,55	166	4,5
Aub 96 1	Auboué 1996 Coinville	0,53	170	5
Aub 96 2	Auboué 1996 rue de Metz	0,45	150	6
Mou 97	Moutiers 1997	0,55	120	3
Ron 99	Roncourt 1999	0,53	140	2,5

ID	Sig_Tot (MPa)	Lrg_G (m)	Lng_P (m)	Lrg_G (m)	Surface (m^2)
Aud 02	10,17	4	55	5	220
Esch 19	17,61	6	70	6	420
StMar 32	15,85	10	12	8	120
Mou 40	10,08	10	10	7	100
Jar 49	11,36	9	11	5	99
Ron 54	14,70	7	80	7	140
Ron 59	16,80	12	12	12	144
Aub 72	12,00	11	70	7	720
Roch 73	15,00	6	13	5	78
Roch 74	14,60	7,5	10	5	75
Crus 77	10,80	11	25	6	275
Vill 82	9,22	8,5	45	5	382
Aub 96 1	10,85	6	7	3	42
Aub 96 2	10,88	12	70	7	840
Mou 97	8,00	12	12	6	144
Ron 99	8,94	6	85	6	510

ID	D_Hydr (m)	El_P	C_Surch	Type
Aud 02	1,86	3,38	1	Brutal
Esch 19	2,76	1,00	3	Brutal
StMar 32	2,73	0,50	3	Brutal
Mou 40	2,5	1,10	1	Brutal
Jar 49	2,48	0,56	1	Progressive
Ron 54	2,59	1,07	2	Brutal
Ron 59	3	0,42	2	Brutal
Aub 72	4,75	0,55	1	Progressive
Roch 73	2,05	0,75	2	Brutal
Roch 74	2,14	0,60	2	Brutal
Crus 77	3,82	0,35	2	Progressive
Vill 82	3,57	0,53	1	Progressive
Aub 96 1	1,62	0,83	2	Progressive
Aub 96 2	5,12	0,50	3	Progressive
Mou 97	3	0,25	2	Progressive
Ron 99	2,8	0,42	2	Progressive

3.2 *Principal Components Analysis (PCA)*

Principal component analysis is an interdependence technique of data analysis in which all variables are simultaneously considered. The general purpose of this analysis is to find a way of condensing the information contained in a number of original variables into a smaller set of new composite dimensions (components) with a minimum loss of information. Hair et al. (1992).

The principal components analysis is based on the analysis of the correlation matrix. In a multivariate space of n dimensions, each variable in the model counts for one dimension. The eigenvalues of the correlation matrix might be though of as the amount of variability that is included in each eigenvector, i.e. the amount of variability included in each component. Depending on the amount of variability that included in each component, we can decide to include only a limited number of components that include 80 or 90% of the variability of the model.

Our objective of using this type of factor analysis was to try to find from all collected variables, the ones that have significant representation of the population of 16 individuals. For this purpose, we have considered the variable *"Type"* as a *passive* variable, i.e. it does not interfere in the definition of the factor model, but to be projected on the resultant factor graph in order to see its place. This technique allowed us to know which observed/calculated variables are correlated with the type of collapse and though could be used in the discriminant process.

Figures 2 and 3 show the plots of *correlation circles,* i.e. projection of the observed variables, over planes defined by "First and Second" components of the factor analysis and "First and Third" components of the factor analysis.

In the principal component analysis, we can also make a projection of the individuals over the different planes defined by different components. The coordinates of each individual present their values with respect to different principal components. Figures 4 and 5 show the projection of individuals over the factorial planes defines by components 1 & 2, and 1 & 3 respectively.

From these projections over the first, second and third components, we were able to remark that:

- The first factorial plane (1 & 2) include 54% of the variability of the model, while the second plane (1 & 3) include 51% of the model variability. Components 1, 2 and 3 altogether include 73% of the model variability.
- From the projection of individuals over the factorial plane 1 & 3, we can see clearly, a visual discrimination between brutal and progressive collapse, which was not the case in the factorial plane 1 & 2. This fact led us to concentrate on the factorial plane 1 & 3 in order to extract the variables that could enhance the discrimination between the individuals.
- The first Component (32% of the variability) is highly correlated with the variables (*W_cum, El_P, D_Hydr, Surface,* and *Lrg_P*).

We have called this component, the resistance of the subsided zone.

- The third component (19% of the variability) is highly correlated with (*Sig_to, H,* and *Lrg_G*). This component could be thought of as the mechanical stress on the pillars.
- We can see clearly that the variable *Defruit* is highly correlated with the passive variable *Type*, and both lie on the quadrant of the circle, which means that they are equally correlated with the first and third components.

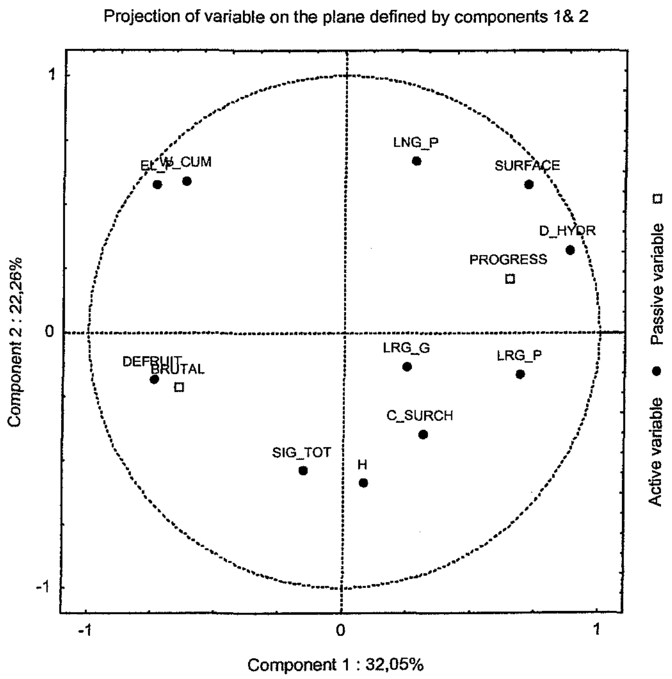

Figure 2. Factor plot of variables over the factorial plane defined by the first two components of the factor analysis

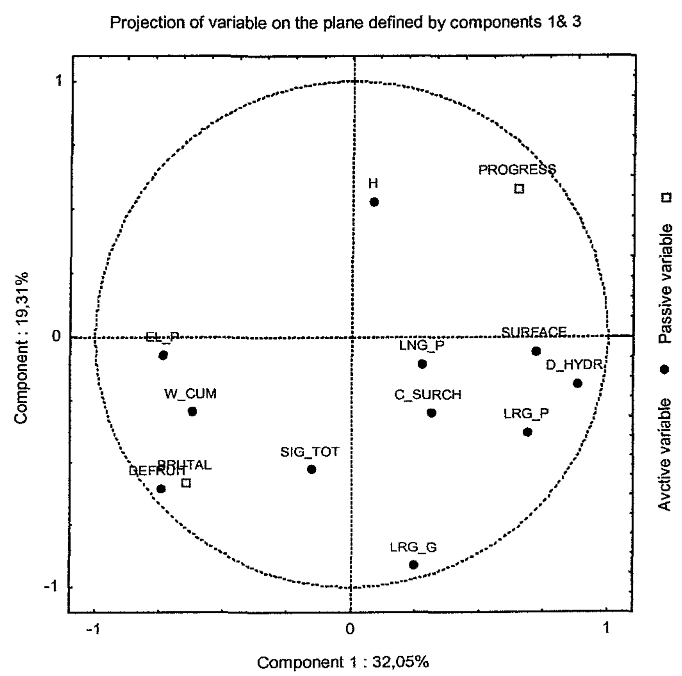

Figure 3. Factor plot of variables over the factorial plane defined by components 1 & 3.

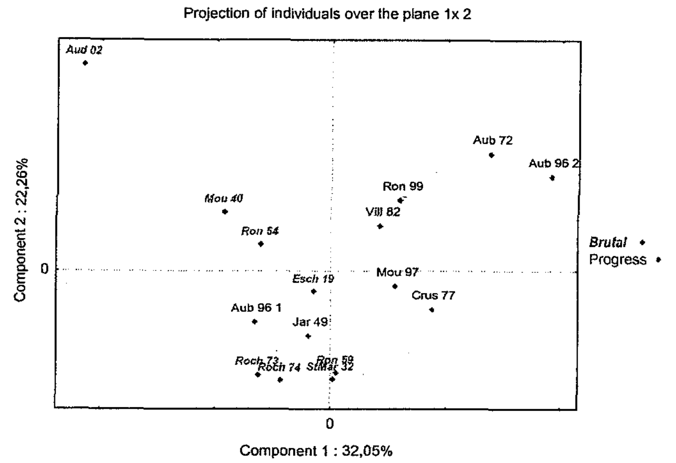

Figure 4. Projection of individuals over the factorial plane 1 & 2

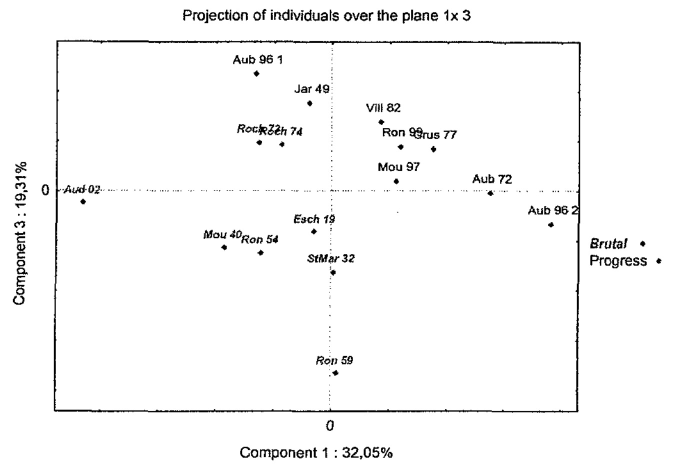

Figure 5. Projection of individuals over the factorial plane 1 & 2

The above mentioned remarks led us to believe that the variables included in these two components (1^{st} and 3^{rd} components), are the ones to be used for the discrimination between the two types of individuals (*brutal and progressive*), and that the variable *Defruit* will be highly favourable for this discrimination.

3.3 *Discriminant Analysis*

The Discriminant Analysis (DA) is the appropriate statistical technique when the dependant variable is categorical and the independent variables are metric Hair et al. (1992).

This technique is widely used in many situations where the objective is to identify the group to which an object belongs.

In our case, the discriminant analysis is to be used in order to define a discriminant function that discriminates the most our population of individuals (collapse) into the two observed groups (brutal and progressive).

As mentioned earlier in the principal components analysis, we were able to define a group of variables (those highly correlated with the first and third components) to be included in the discriminant analysis and that the variable *Defruit* is most likely, the best one to start with.

Discriminant analysis could be performed in a *simultaneous* approach, i.e., all independent variables are considered concurrently, or it could be done in *stepwise* approach, i.e. variables are entered one by one into the discriminant function depending on their discriminating power.

The simultaneous approach is appropriate when, for theoretical reasons, the analyst wants to include all the independent variables in the analysis and is not interested in seeing intermediate results based only on the most discriminating variables.

The stepwise approach begins by choosing the single best discriminating variable. The initial variable is then paired with each of the other independent variables one at a time, and a second variable is chosen. The second variable is the one that is best able to improve the discriminating power of the function in combination with the first variable. The third and any subsequent variables are selected in a similar manner. As additional variables are included, some previously selected variables may be removed if the information they contain about group differences is available in some combination of the other included variables. The stepwise approach is useful when the analyst wants to consider a relatively large number of independent variables for inclusion in the function. By consequentially selecting the next best discriminating variable at each step, variables that are not useful in discriminating between groups are eliminated and a reduced set of variables is identified, and the reduced set typically is almost as good as, and sometimes better than, the complete set of variables.

Although our main intention, in the current case study was to be able to discriminate between the two groups of collapse with minimum number of variables, we have performed the discriminant analysis in both simultaneous and stepwise approaches in order to compare with the different results if any.

In order to be able to judge on the quality of discrimination, we have adopted the cross validation test, which consists of eliminating one individual from the analysis, finding out the discriminant function without this individual and then reclassifying it according to the resultant function. If it is classified correctly, then the test is successful, if not, the test is not successful. This procedure is done over all the individuals and results of this test are represented as a percentage of success.

3.3.1 *Results of the discriminant analysis with Simultaneous approach*

Figure 6 present a graph of projection of individuals and the centre of gravity of each group, over the discriminant function defined by all the variables (simultaneous approach). This graph is to be regarded as a one-dimensional graph as the discriminant function has only one dimension (brutal and progressive). The Y axis is plot only for presentation purpose only and does not have any significance.

Although, as we can see in Figure 6, that the two categories of individuals are discriminated on the graph, the simultaneous approach function failed to satisfy the cross validation test. Table 2 represents the results of this test.

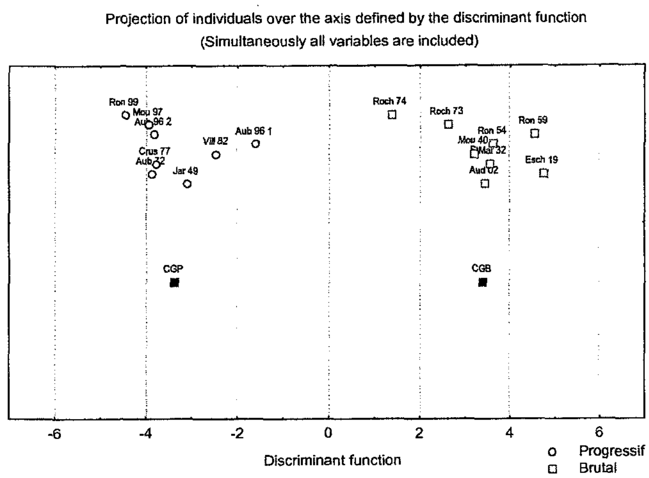

Figure 6. Individuals projected over the discriminant function resultant of the simultaneous approach.

Table 2. Results of the cross validation test for the simultaneous approach's discriminant function.

	Observed class	Predicted class Brutal	Progressive	Total
Original data	Brutal	8	0	8
	Progressive	0	8	8
%	Brutal	100,0	0,0	100,0
	Progressive	0,0	100,0	100,0
Test de cross validation	Brutal	6	2	8
	Progressive	2	6	8
%	Brutal	75,0	25,0	100,0
	Progressive	25,0	75,0	100,0

3.3.2 *Results of the discriminant analysis with stepwise approach*

After several trials with different sets of variables chosen according to experts knowledge of the sites and its characteristics with combination of the results of the principal components analysis, we were able to define a discriminant function using the stepwise approach and including only 7 variables (*Defruit, Sig_Tot, H, W_cum, D_Hydr, Lrg_G, C_Surch*).

Figure 7 shows the projection of individuals and the centre of gravity of each group, over this discriminant function. This graph, as for the one defined by the simultaneous function has to be regarded as a one-dimensional graph, and that the Y axis does not have any significance and was only introduced for purpose of clarity of illustrations.

In Table 3 the results of the cross validation test are presented. We can see from Table 3 that this function defined with only 7 variables in a stepwise manner pass with 100% this test and could be considered as a better discrimination function than the one done in a simultaneous manner.

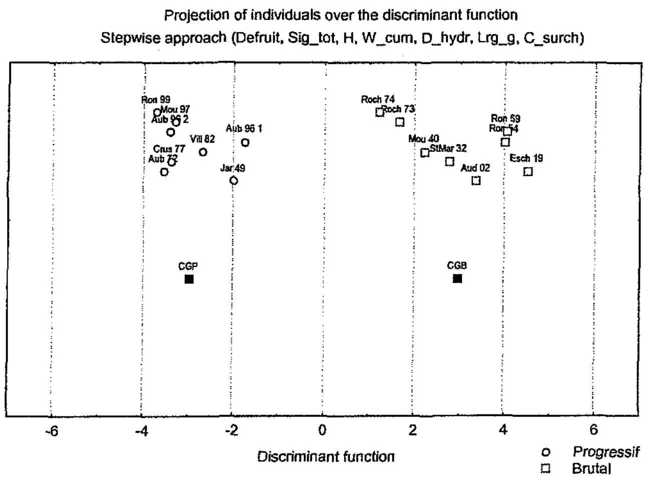

Figure 7. Individuals projected over the discriminant function resultant of the stepwise approach.

Table 3. Results of the cross validation test for the stepwise approach's discriminant function.

	Observed class	Predicted class Brutal	Progressive	Total
Original data	Brutal	8	0	8
	Progressive	0	8	8
%	Brutal	100,0	0,0	100,0
	Progressive	0,0	100,0	100,0
Test de cross validation	Brutal	8	0	8
	Progressive	0	8	8
%	Brutal	100,0	0,0	100,0
	Progressive	0,0	100,0	100,0

4 CONCLUSIONS

The problem of surface collapse is one of the major problems that concern all abandoned mining basins that have been exploited over the last century (XXth century).

In our case, the problem concerned an area of 1500 square kilometres and the impact of surface collapse on the population is a major concern to the regional authorities.

In collaboration with mining, geotechnical, and geological experts we started this study as a pilot study that could show the importance of data analysis in determining the type of expected collapse in absence of other geological criteria.

We were able to define, with the help of site's experts; a discriminant function that could be used in the discrimination of new studied zones, or zones of high importance to the society.

This analysis could lead to the definition of zone risk map where we can provide areas of likely to subside in a brutal way and others likely to subside in a progressive way.

This method of analysis is highly recommended in similar cases where geological or geotechnical factors are not enough.

We have also to mention that due to the limited number of individuals (we have succeeded to find valid data for only 16 accidents over 100 years), we were not able to perform further tests on the produced function, and has to be used only in the context and within the limits of the geological and geotechnical parameters of the Lorraine iron basin.

5 REFERNCES

Elshayeb, Y. 2000. Prévision des conséquences des affaissements miniers dans les mines de fer de Lorraine : Étude Méthodologique pour la détermination du type d'effondrement attendu : Analyse des données détaillée et élaboration d'une fonction discriminante. Rapport Gisos-Auxirbat recherche. École des Mines de Nancy.

Hair, J.F. & Anderson, R.E. & Tatham, R.L. & Black, W.C. 1992. Multivariate data analysis with readings third edition. Macmillan Publishing Company.

Tincelin, E. 1959. Effondrements spontanés de certains quartiers constatés dans les mines de fer de l'est. Rapport École des Mines de Paris.

Tincelin, E. & Sinou, P. 1962. Effondrements brutaux et généralisés–Coups de toit. Revu de l'industrie minérale. April 1962.

Tincelin, E. 1995. Essais d'explication des grands effondrements spontanés survenus dans les mines de fer depuis le début du siècle : conclusions pratiques à en tirer pour l'exploitation. Rapport École des Mines de Paris.